On the EEG-based Automated Detection of Alcohol Dependence

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Abstract: *Power and magnitude square coherence estimates evaluated for EEG of alcoholics and control participants were used to attempt an automated discrimination of individuals suffering alcohol dependence. The estimates were obtained for non-overlapping consecutive EEG fragments of 0.5 second duration with parametric analyzers and used as features for Euclidean, Fisher, and Regression-based classifiers. Implementing the leave-one-out cross-validation technique, the highest unbiased classification accuracy, sensitivity of 66.45% and selectivity of 67.12%, was observed from the Regression-based classifier when θ-rhythm power estimates for all EEG electrodes were used as classification features.*

Keywords: *EEG, Power, Coherence, Euclidean, Fisher, Regression classifiers.*

Introduction

Compared to other imaging techniques – such as magnetic resonance imaging (MRI), positron emission tomography (PET), and magnetoencephalography (MEG) – electroencephalography (EEG) offers superior temporal resolution (except for MEG) at a significantly lower cost. It may serve as a convenient and accurate tool for disease screenings within large populations. Quantitative analysis of the electroencephalogram (QEEG) has been extensively used in epilepsy research [3, 17, 18], in studies of various sleep disorders [26, 27], in Alzheimer disease research [10, 21], in studies of head injuries [4, 16, 25], etc.

On the other hand, acute consumption of ethanol alcohol can be characterized by short-term effects on an individual; ranging from impaired judgment and coordination through increased aggressiveness to dizziness, nausea, stomach dysfunctions, etc. Prolonged heavy consumption of alcohol may lead to long-term (permanent) effects including: permanent damage to vital organs, high blood pressure, various types of cancer, nutritional deficiencies, epigenetic changes, impairment of memory and cognition, etc. Evidences suggest that both short-term and long-term effects of alcohol may produce detectable changes in subject's electroencephalogram.

Spectral analysis has revealed the following (short-term) effects of acute alcohol consumption on spontaneous EEG: an increase in the α-rhythm (8-12 Hz) power induced by moderate doses of alcohol [11]. More specifically, reports indicate significant increase in the power of α_1-rhythm (8-10 Hz) due to alcohol administration [5]. Larger doses of alcohol may produce an increase in lower (i.e., below 8 Hz) EEG rhythms [14].

The resting EEG of alcoholics has been characterized by an increased power in δ-rhythm (0-4 Hz) [13, 23], an increased power in θ-rhythm (4-8 Hz) [23], a reduced power in α-rhythm (8-12 Hz) [5, 14, 6, 7, 12, 15, 19], and an increased power in β-rhythm (12-30 Hz) [13, 19, 1, 8]. Moreover, similar changes were also observed in the EEG of offspring from alcoholics [6, 19]. Another report [1] suggests reduced power in δ- and θ-rhythms observed in alcoholics. Perhaps, this contradiction might be attributed to differences in data analysis.

EEG processing techniques other than spectral analysis were also employed in alcohol-related studies. Applications of connectivity metrics showed reduced synchronization in α (8-12 Hz) and β_1 (12-20 Hz) rhythms evidenced in the EEG of heavily drinking individuals (i.e., 21 alcoholic drinks per week or more) compared to lightly drinking participants [2]. Bilateral, intra-hemispheric, and posterior coherence were found significantly higher in δ-rhythm [13] and in α- and β-rhythms in alcohol dependent participants [28]. On the other hand, Kaplan and coworkers reported decreased coherence for rhythms above δ being observed in alcoholics [13].

We have recently demonstrated that spectral and coherence estimates were generally lower for alcoholics than for controls while evaluated for low EEG rhythms. Kruskal-Wallis's one-way analysis of variance indicated these alterations as statistically significant [24].

While utilizing the same EEG data and the results obtained in the previous study [24], the present project targets an automated classification between alcoholics and control individuals. The discrimination will be based on spectral and coherence metrics evaluated from their EEG and for the following rhythms: δ (1-4 Hz), θ (4-8 Hz), α_1 (8-10 Hz), α_2 (10-12 Hz), β_1 (12-20 Hz), β_2 (20-30 Hz), γ_1 (30-40 Hz), and γ_2 (60-50 Hz).

Methods

EEG data for this project were obtained from an open database and were originally donated by Dr. Henri Begleiter at Neurodynamics Laboratory, State University of New York Health Center, Brooklyn. The data have been collected from male alcoholic subjects of mean age 35.83, standard deviation 5.33 and range 22.3-49.8 years, and from the male controls with mean age 25.81, standard deviation 3.38, and range of 19.4-38.6 years. EEG data were recorded from a set of 62 electrodes placed according to the extended 10/20 International montage; trails with excess of eye and body movement were excluded. These EEG data were used previously in alcohol-related studies [23, 24, 29, 30]. The "Cz" channel was excluded from present study since it was used as the recording reference.

EEG processing

Spectral and coherence estimates were obtained for consecutive 0.5 second-long EEG fragments using parametric techniques. The detailed description of EEG processing may be found elsewhere [24]. Therefore, two discrete data sets were used in the present project: Spectral and Coherence sets. Each set consists of two groups: Alcoholics and Controls. Within each set, the alcoholic group contains 17.953 samples for each EEG rhythm and EEG channel, while the control group inludes 10.575 samples.

We have demonstrated previously that differences in EEG power and coherence between the alcoholics and non-alcoholics groups are statistically significant for selected EEG channels and rhythms [24]. The main objective of present work was to evaluate various classification

techniques aimed at an automated discrimination between alcoholics and non-alcoholics based on their EEG. Numerous techniques have been proposed for classification (or pattern recognition) over the past 50 years. One of such techniques, referred to as pattern matching, provides the exact match selected from the pre-existing matches. Another technique, pattern recognition, classifies input signals into one of the classes according to the pre-defined rules. Pattern recognition usually consists of two stages; feature extraction and pattern classification. During the feature extraction process, specific features are produced from a large number of available initial measurements by linear or non-linear transformation. The objective of the classification stage is to assign an *n*-dimensional features vector X to one of the classes using the selected algorithm.

Present paper is aimed at evaluating performance of three pattern classification methods – Euclidean distance classifier, Fisher classifier, and Regression classifier – applied to the spectral and coherence estimates obtained for EEG of alcoholics and control subjects as described previously [24].

Euclidean distance classifier

The unknown features vector X defined as follows

$$X = (x_1, x_2, \ldots, x_n)^{\mathrm{T}} \tag{1}$$

is classified into one of the Z classes according to the Euclidean distance to the means of these classes $M_1, M_2 \ldots M_Z$ [20]. The Euclidean distance between the vectors X and M_r is evaluated as:

$$D_{X,M_r} = \|X - M_r\| = \sqrt{(X - M_r)^{\mathrm{T}}(X - M_r)} \tag{2}$$

In the case considered here, only two classes are assessed. M_1 and M_2 are the sample means of two classes of features evaluated for alcoholics and controls respectively. The discriminant function $h(X)$ is evaluated next as follows:

$$h(X) = D_{X,M_1} - D_{X,M_2} = X^{\mathrm{T}}V_E + V_0 \tag{3}$$

where

$$V_E = M_1 - M_2 \tag{4}$$

and

$$V_0 = -\frac{(M_1 + M_2)^{\mathrm{T}} V_E}{2} \tag{5}$$

If the sign of the discriminant function in (3) is negative, the vector X is assigned to the alcoholics group; otherwise, it is classified to the control group.

Fisher classifier

The Fisher classification procedure [20] is similar to the Euclidean Distance method except that the variance is considered also. Therefore, the discriminant function is:

$$h(X) = X^{\mathrm{T}}V_F + V_0 \tag{6}$$

Here

$$V_F = \hat{\Sigma}^{-1}(M_1 - M_2) \tag{7}$$

Sample covariance estimate:

$$\hat{\Sigma} = \frac{1}{N_1 + N_2 - 2}\sum_{i=1}^{2}\sum_{j=1}^{N_i}(X_j - M_i)(X_j - M_i)^{\mathrm{T}} \tag{8}$$

where X_j is the j-th training set observation

and

$$V_0 = -\frac{(M_1 + M_2)^{\mathrm{T}}V_F}{2} \tag{9}$$

If the sign of the discriminant function (6) is negative, X is assigned to the class 1 (alcoholics); otherwise, it is associated with the class 2 (controls).

Regression analysis

In general, regression analysis establishes a functional relationship f between the input vector X, the weight vector β, and the output vector Y of the model.

$$Y = f(X, \beta) \tag{10}$$

In present work, a locally weighted regression (LWR) model proposed by Godoy and colleagues [9] was implemented. The decision boundary was selected experimentally as 1.7 to yield high classification accuracy. The detailed description of the LWR algorithm can be found in [9].

Classifiers' performance evaluation

During the classifiers' performance evaluation, the group of alcoholics was assumed as the "unusual class" and the control group was considered as the "normal class". Therefore, the classification problem was reduced to the detection with the unusual class being positives and the normal class – negatives. Thus evaluating the classifier's correct detections of an abnormal condition (True Positive) and the correct detections of a normal condition (True Negative), the classifier's performance (i.e., percentage of correct classifications) may be described by the following descriptors [22]:

$$Sensitivity = 100\% \frac{True\ Positive}{Total\ Abnormal} \tag{11}$$

$$Specificity = 100\% \frac{True\ Negative}{Total\ Normal} \tag{12}$$

To evaluate the classifier performance, a leave-one-out cross-validation was implemented using MATLAB. The classification accuracy was estimated according to (11) and (12).

Results

Initially, all available EEG channels were used to evaluate the classification metrics (i.e., spectral or coherence estimates). The corresponding classification accuracies – sensitivity and specificity – are reported in Fig. 1 as functions of EEG rhythms and for three classifiers.
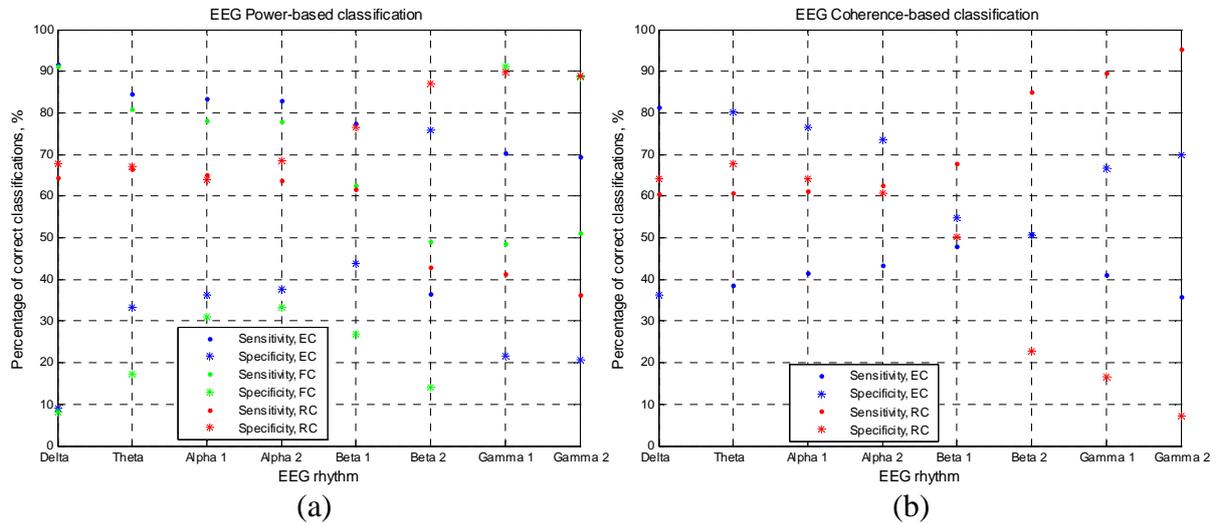

Fig. 1 Percentages of correct classifications (sensitivity and specificity)
of Euclidean (EC), Fisher (FC), and Regression Classifiers (RC)
using EEG Power (a) and Coherence (b) as the classification features

As expected based on our previous results [24], classification performance varies when EEG power and coherence evaluated for different rhythms were used as classification features. It is also seen in Fig. 1 that Euclidean and Fisher classifiers show biased, towards one of the groups, discrimination results. This tendency can also be observed in the regression classifier when using the EEG rhythms from β_1 to γ_2. For the lower rhythms, on the other hand, its classification accuracy ranges from approximately 60% to approximately 70%, which is not sufficient for any practical use. Therefore, we conclude that, while the results produced by the regression classifier for low EEG rhythms are promising, no reliable detection of alcoholics was achieved yet when using power and coherence estimates for all available EEG channels and while implementing the above classifiers.

When using Magnitude Square (MS) coherence estimates as the classification features, Fisher classifier assigned all subjects to the alcoholics group; therefore, the corresponding results were not included in Fig. 1(b). Perhaps, this bias may be explained considering that the Fisher classifier is optimal for Gaussian distribution of classification metrics. A histogram of MS coherence estimates is shown in Fig. 2.
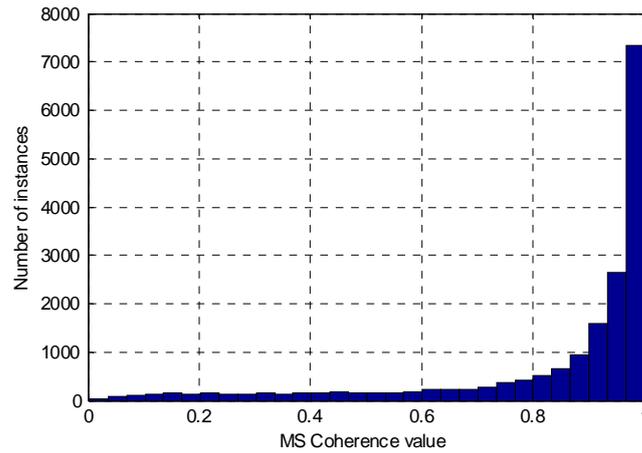
Fig. 2 Histogram of the MS coherence estimates
between C_4 and Fp_1 EEG electrodes and for θ-rhythm

Since a histogram approximates the shape of the probability density function, we may conclude from Fig. 2 that MS coherence is certainly not normally distributed. As a consequence, Fisher discriminator may fail when using coherence estimates as classification features. We further hypothesize that Euclidean and Regression classifiers are more robust regarding the features' distribution and, therefore, are more suitable for the MS coherence.

A modified detection procedure was considered next. We observed previously that power and coherence estimates evaluated for specific EEG rhythms and for particular electrodes may show statistically significant differences between alcoholics and control groups [24]. Therefore, we hypothesize that various EEG electrodes may contribute to higher (or lower) classification accuracy within different rhythms. Thus, only the EEG channels, for which the corresponding metrics were deemed statistically different between two groups (electrode mask #1), were included in the classification next. The corresponding results for power and coherence are illustrated in the left panels of Fig. 3 and Fig. 4.

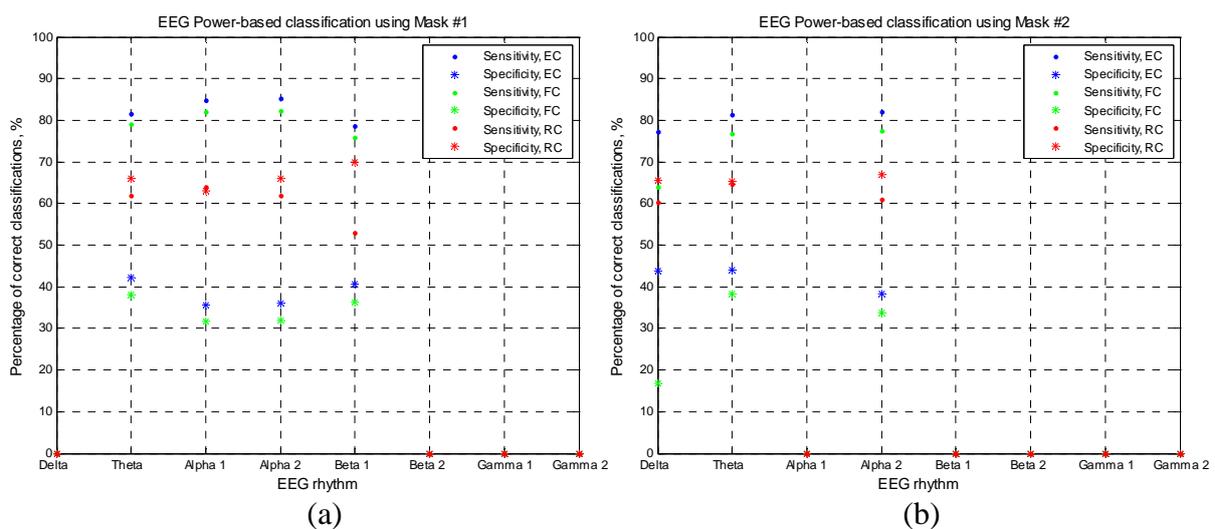(a)   (b)

Fig. 3 Percentages of correct classifications (sensitivity and specificity)
of EC, FC, and RC using EEG Power estimates for selected EEG channels
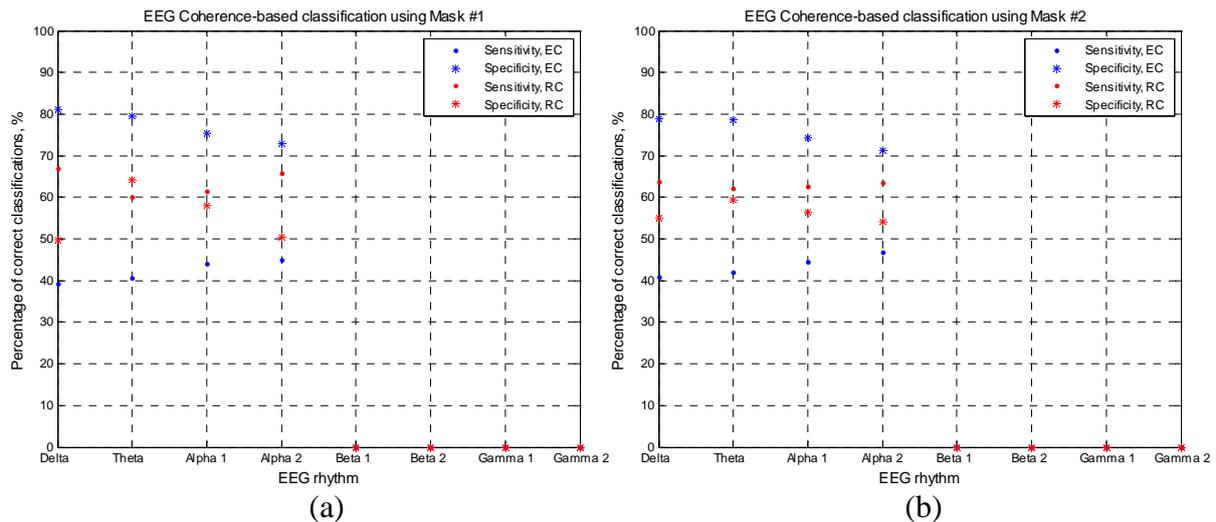(mask 1 – (a) and mask 2 – (b)) as the classification features

Fig. 4 Percentages of correct classifications (sensitivity and specificity)
of EC, FC, and RC using EEG Coherence estimates for selected EEG channels
(mask 1 – (a) and mask 2 – (b)) as the classification features

For comparison, only the EEG channels contributing to the most different average power and coherence between the groups (electrode mask #2) were selected for classification as an alternative approach. The corresponding results are shown in the right panels of Fig. 3 and Fig. 4.

As previously, Fisher classifier appeared biased towards one group when using coherence estimates as classification features. The corresponding results were excluded in Fig. 4.

We further observe in Fig. 3 and Fig. 4 that, as previously, Euclidean and Fisher classifiers generally produced biased results. Comparing Fig. 1 and Fig. 3, Fig. 4, we conclude that judicious selection of EEG electrodes for the analysis does not contribute to increase in classification accuracy since both sensitivity and specificity are not considerably different between the results obtained for all electrodes and for the selected EEG channels only.

Conclusions
We have previously demonstrated that parametric spectral and coherence estimates obtained for consecutive 0.5 s-long EEG fragments and evaluated for low EEG rhythms were generally lower for alcoholics than for control individuals. Furthermore, Kruskal-Wallis one-way analysis of variance deemed these alterations as statistically significant.

Although our previous results indicate that an automated detection of alcohol dependence may be possible based on the EEG power and coherence estimates, we conclude that no such detection was reliably achieved using the classification techniques assessed. We also observed that Fisher classifier produced biased results preferring one of the groups when the coherence estimates were used as the classification feature. Perhaps, this bias may be explained by a non-Gaussian distribution of the experimental data.

Our observation of judicious selection of EEG channels not leading to noticeable improvements in classification may be restated as follows. Including in the classification EEG channels not contributing to statistically significant differences between the groups is not likely to affect the classification accuracy, since adding irrelevant features should not reduce

the classifiers' performance. On the other hand, if only the EEG channels contributing to statistically significant differences between the groups are considered, classifier dimensionality is reduced and a more computationally efficient classifier may result.

Nevertheless, the highest unbiased classification accuracy, sensitivity of 66.45% and selectivity of 67.12%, was observed from the regression-based classifier when θ-rhythm power estimates of all EEG electrodes were used as the classification features.

We conclude that simple classification techniques, such as Euclidean and Fisher methods, are not suitable for reliable detection of alcohol dependence when using the EEG power and coherence estimates as classification features. On the other hand, a more advanced procedure, regression-based classifier, yielded better discrimination accuracy, although still not quite satisfactory for the majority of practical applications. Therefore, we hypothesize that more complicated discriminators, such as neural network or support vector machine classifiers, may lead to the improved classification results.

Acknowledgements

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